Updating of FEM Models for Laboratory Tests on Cylindrical Panels and Their Reliability Analysis by the Hybrid FEM/ANN Monte Carlo Method

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Abstract

The paper develops the ideas from [5] as well as continues [2] which show how ANN may be used in probabilistic evaluation of the reliability of a structure simulated by the classic Monte Carlo (CMC) method. The paper deals with the reliability analysis of a cylindrical shell described in [1]. Samples for MC simulation were generated with the use of ANN. The set of patterns for network training and testing have been calculated with FEM – COSMOS/M programme. The analysis of times of calculations has confirmed a very large numerical efficiency of hybrid CMC.

Keywords: reliability, cylindrical shell, laboratory test, finite element method (FEM), back-propagation neural network (BPNN), Monte Carlo (MC) method, updating, hybrid method

1. Introduction

There are two basic problems of the reliability analysis of structures [1]. The first one corresponds to a statistically representative sets for the probabilistic analysis. The second problem is related to a numerically efficient method for the reliability analysis. In the presented problem only three cylindrical panels were tested. That is why computer simulations, carried out by means of an updated FE code, cf. [2], might generate an appropriate input set of data. The method of updating is related to the introduction of control parameters, which are calibrated by experimental results taken from laboratory tests [3].

The second problem corresponds to the application of the Hybrid Monte Carlo Method, see [4, 5]. In this method the updated FE program is applied for the generation of patterns for the training and testing of artificial neural networks (ANNs). The trained ANN can be explored for the fast computation of Monte Carlo (MC) trials.

2. Laboratory tests on cylindrical panels

A scheme of the tested panel is shown in Fig. 1. In the scheme the basic control parameter is shown corresponding to the stiffness of equivalent bars modelling the horizontal shift-ability of the screws blocking the vertical displacements of the supporting beams.

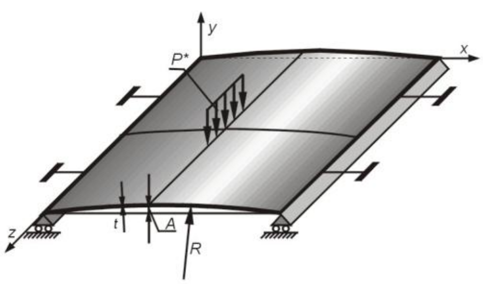

Figure 1: Scheme of cylindrical shell

Three panels were tested by means of the test stand shown in Fig.2. The rectangular projection of the panel midsurfaces had dimensions $L \times B$ = 472× 470 mm, thickness t = 5 mm and curvature radius R = 1380 mm. Mechanical parameter mean values were adopted as E = 205 GPa, R_e =274 MPa, ν = 0.3. The panel was placed between supporting plates of thickness t_{BP} = 40 mm, screwed to the lower crosshead plate of the test stand. All details of the tests carried out are described in [1].

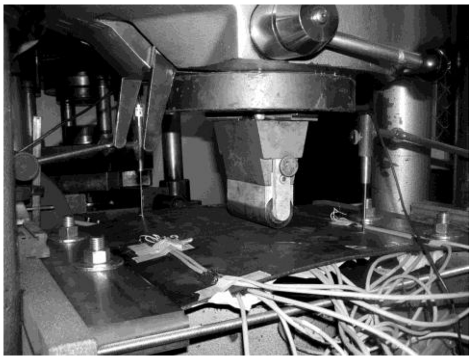

Figure 2: Test stand

3. Updating of a FEM model and generating of patterns

The boundary plate (BP) was included in to the FE mesh shown in Fig. 3. The HMH material with isotropic strain hardening was assumed. On the base of introductory tests performed on three shell panels, the average stiffness of equivalent lateral bars E_0 = 5.0 $\times 10^5$ GPa can be adopted. The beam and shell FEs were applied in the COSMOS/M code, suitable to the nonlinear buckling analysis. The next control parameters were selected as those which value changes are sensitive for the current deformation of the tested shells. The following three control parameters were selected: in the FE model: A – the approximated deflection of the cylindrical panel midsurface, R_e – yield stress; T – cross-section of the equivalent lateral bar. These parameters were found after a deep analysis of the introductory lab tests.

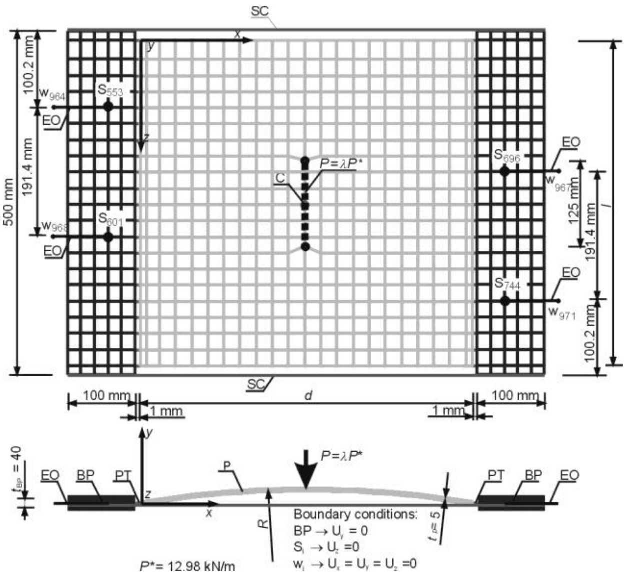

Figure 3: FEM model

Looking at the sensitivity of experimental equilibrium paths (see for instance a path in Fig. 4) the mean values of the pdf distributions for the random values of the control parameters and estimation of variances were estimated. The normal pdf were assumed for material yield point R_e, deflection parameter A, and lognormal pdf for cross-section T.

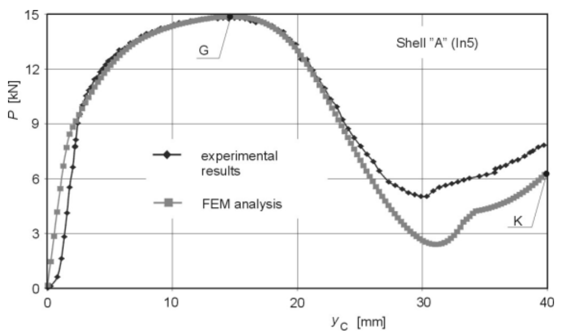

Figure 4: Shell deflection equilibrium path

4. Reliability analysis

In order to generate MC trials ANNs were formulated to simulate values of ultimate load factor λ_{ult} as a function of the random vector of inputs $\mathbf{X}^R$, i.e. the ANN performs mapping:

$$\mathbf{X}^R \xrightarrow{\text{ANN}} \lambda_{ult} \tag{1}$$

It was assumed that the problem is considered as stationary, i.e. independent of time. Networks of $N – H – 1$ architecture were used in CMC simulation, where: N – number of inputs corresponding to random variables, H – number of binary sigmoid neurones in the hidden layer, 1 – scalar output corresponding to the ultimate load factor λ_{ult}. The patterns for network training and testing were computed by the updated FEM – COSMOS/M programme. Single parameter load $P_{ult} = P^*\lambda_{ult}$ was considered.

Two cases of the vector of random variables $\mathbf{X}^R$ were adopted, i.e. case 1) $\mathbf{X}^R = \{A, R_e, T\}$ with components corresponding to those described above in Point 2, Case 2) $\mathbf{X}^R = \{A1, A3, T, R_e\}$, where: $A1, A3$ – amplitudes of trigonometric functions approximating the shell midsurface In both cases three families of networks were trained, each of which was trained with a different set of training patterns with the number of elements: $L_{11} = 3^3 = 27$, $L_{12} = 5^3 = 125$, $L_{13} = 7^3 = 343$ for the case 1 and $L_{21} = 3^4 = 81$, $L_{22} = 4^4 = 256$, $L_{23} = 5^4 = 625$ for the case 2. The sets of $T_k = 100$ testing patterns were randomly selected from the 3D cubs of ribs equal to 6 sigma bars.

Two cases of MC simulation were performed. The cases differed the formulation of the load: Case I) – load P is a determined value, Case II) – load P is a random variable of average $\overline{P}$ and coefficient of variation $V = 0.1$. Six best networks (one from each family) were selected for MC simulation. Two reliability curve, selected from among computed twelve structural reliability curves, are shown in Fig. 4. It was shown in this figure that to the considered two load cases gives values of load factors close to each other. For instance for desirable probability $\overline{q}(\overline{P}) = \overline{q}(P) = 0.9$ the corresponding mean values of loads are $\overline{P} \approx 10.73$ kN and $P \approx 11.09$ kN structural reliability curves were obtained.

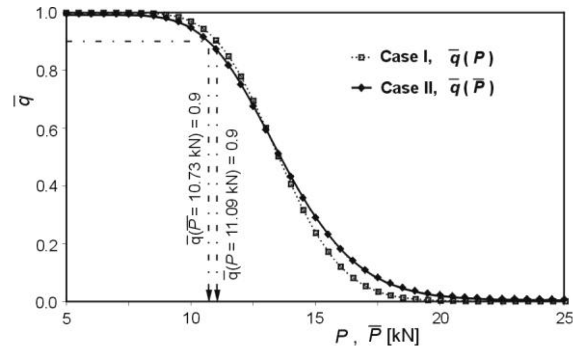

Figure 5: Structural reliability curves q (P)

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